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RESEARCH ON PERSONALIZED LEARNING RECOMMENDATION SYSTEM BASED ON MACHINE LEARNING ALGORITHM

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Abstract. The educational system has started to implement more individualized material from conventional functions in recent years due to the ongoing advancements and developments in science and technology, particularly the continuing growth of artificial intelligence, machine algorithms, and other technologies. The standardized approach to teaching used by conventional educational institutions frequently ignores the individual requirements and learning preferences of every student. To improve learning outcomes, a system of education that is personalized and enhanced by algorithms using machine learning can offer individualized learning materials and suggestions that reflect every student's educational background, interests, and skills. Additionally, machine learning methods may offer immediate feedback on student achievement and modify instructional strategies in response to that feedback. Making sure AI is employed to promote higher education's overarching objectives, like encouraging creativity and critical thinking, as opposed to merely eliminating chores and boosting effectiveness, is another difficulty. This paper examines over the several ways that artificial intelligence (AI) and the Optimized Collaborative Filtering Algorithm are being used in higher education. It also proposes an approach for increasing students' cognitive abilities and compares it with different methods that are currently in use. It has been demonstrated that, in comparison to other models, the suggested model performs better by achieving 95% recall and 99% testing accuracy.

Key words: Personalized learning, recommendation system, machine learning, students, educational institutions

1. Introduction. The rise of technological advances in educational institutions is leading to innovative teaching and learning, with artificial intelligence and intelligent instruction taking the lead. This trend is expected as education becomes more and more digitized [1, 10, 5]. The time of artificial intelligence is confronted with a new challenge as big data in education grows and needs to be analysed to ensure correct forecasting. Education-related large data analysis and forecasting can be satisfied by machine learning, a significant area of artificial intelligence. The suitableness of machine learning and smart instruction are thus explored via an examination of the method, the thing, particular methodologies, and users of machine learning.

There are difficulties and moral issues with using AI in higher education. Maintaining the impartiality and precision of AI systems while eliminating possible prejudices is one of the major difficulties. Challenges exist around the confidentiality of student information in addition to the possibility that AI will eventually take the role of human educators and assistance personnel [20, 13]. Making sure AI is applied in a manner that advances the general objectives of higher learning, like encouraging innovative thinking and problem-solving, as opposed to only becoming used for task automation and productivity gains, is a further challenge [6].

With the widespread use of the latest iterations of computer networking, wireless communication, cloud computing, the Internet of Things (IoT), and artificial intelligence (AI), we are entering an entirely novel phase of smart technological advances and extensive data mining uses. All facets of our life are being controlled by artificial intelligence, machine learning, and big data processing, which are driving global digital transformation [12, 2]. New teaching and learning approaches have been implemented in higher education institutions because of these groundbreaking advancements in information technology.

The expanding breakthroughs in artificial intelligence and machine learning, in particular, have made the incorporation of personalized learning in educational systems increasingly important. Traditional teaching methods frequently produce less than ideal results since they do not take into account each student's particular demands and learning preferences. In order to provide an extremely flexible learning environment, this

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study suggests a novel application of an Optimized Collaborative Filtering Algorithm along with other AI-driven techniques. These technologies allow for the real-time assessment and modification of teaching tactics based on immediate feedback on student performance. They also provide personalized learning materials and recommendations depending on each student's academic background, interests, and skills.

Nevertheless, there is still work to be done in utilizing AI to improve more general educational objectives like encouraging creativity and critical thinking, in addition to efficiency. This study examines the use of AI in higher education in a variety of contexts, offering a novel strategy to improve cognitive capacities and providing empirical support for its superiority over current models. The purpose of this study is to demonstrate how contemporary AI implementations can overcome conventional constraints and provide notable gains in educational efficacy and customisation.

This study investigates a variety of machine learning approaches, such as the Optimized Collaborative Filtering Algorithm, for recommending appropriate models of recommendation for use in higher education settings. These models assist students in identifying their true focus and ability. Additionally, it enhances the kids' cognitive capacities and attitudes in general. The main contribution of the proposed method is given below:

1. An innovative AI algorithm is presented to enhance the learning capacity of students in higher education.
2. The suggested algorithm makes it easier to find, read, and grasp a text piece in large data quickly and in real time.
3. The suggested algorithm stresses pupils' quality and self-worth while simultaneously enhancing their cognitive abilities.
4. In addition to outperforming these models in many ways, it is demonstrated that the suggested algorithm performs better when compared to other common reference models, such as the Gram-CF, CNN-CF, and CNN recommendation models.

The rest of our research article is written as follows: Section 2 discusses the related work on various personalised recommendation system and Machine Learning Algorithms. Section 3 shows the algorithm process and general working methodology of proposed work. Section 4 evaluates the implementation and results of the proposed method. Section 5 concludes the work and discusses the result evaluation.

2. Related Works. Even while artificial intelligence has advanced significantly in the present, it is still in the early stages of integrating with learning and instructional methods and is still far from a mature state. Investigations on the creation and utilization of technological advances has gained a lot of interest recently due to the cases and study findings of the current coupling of artificial intelligence with educational systems both domestically and internationally. Researchers have focused particularly on the four main uses of artificial intelligence in higher education, which are "intelligent learning guide structure, automatic evaluation system, educational games, and educational robots" [8, 3, 19, 7]. Additionally, it is the primary approach taken by educators working in fundamental education.

Numerous methodologies have been suggested in the field of individualized learning route generating study. Personalized learning path generating techniques based on deep learning have also drawn a lot of interest [4]. The neural collective filtering method is a popular recommendations technique that effectively handles limited data as well as cold start issues by embedding knowledge on users and products using neural networks. Scholars have also been experimenting with using neural collective filtering methods to solve path generation problems in customized educational path creation [9]. Neural collective filtering techniques, for instance, are employed to create individualized learning paths by predicting learners' interests and level of knowledge mastery [15].

Additionally, creating a personalized learning path makes extensive use of cognitive diagnostic tools [16]. Cognitive diagnostic methods seek to determine and assess the cognitive level of learners to assist them in identifying their learning deficiencies and problems and to offer appropriate educational recommendations and assistance [11]. By combining cognitive diagnostic approaches with neural collaborative filtering computations, it is possible to generate individualized learning paths by more effectively recommending points of knowledge and learning materials that align with learners' interests and cognitive levels [14].

Choosing into account the significant influence on utilizing the Internet, the abundance of chances for utilizing new skills and more complex behavioural patterns, and the scientific foundation that artificial intelligence

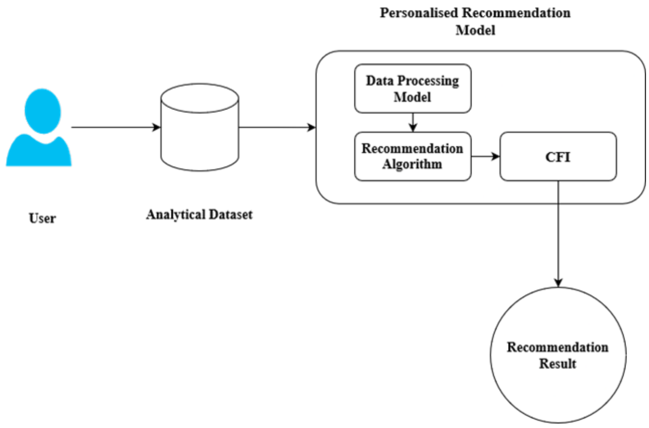

Fig. 3.1: Architecture of Proposed Method

contributes to, it improves students' university education by expanding the growth of their educational requirements [18]. Additionally, AI, communication, and big data support the real-time provision of constructive cultural and educational suggestions to users, that can help satisfy university students' expanding needs for growth [17]. Conversely, the use of AI in educational institutions gives schools and universities the chance to build amicable relationships with their students and can, in certain cases, enhance their sense of identity and self-worth.

3. Proposed Methodology. The proposed methodology for Personalized learning recommendation system based on machine learning algorithm based on artificial intelligence (AI) and the Optimized Collaborative Filtering Algorithm. Initially, the higher education dataset is collected and then the data is pre-processes. Next the Personalized learning recommendation system is trained by using Optimized Collaborative Filtering (CFI) Algorithm. In figure 3.1 shows the architecture of proposed method.

3.1. Construction of Personalized Learning Recommendation System. The rise in popularity of online learning has raised the bar for intelligent resource recommendation, with students, instructors, and administrators serving as the system's user objects. The latter involves an evaluation of users and resources, whereas the first two are primarily concerned with individualized choice of resources and recommendations for instruction. The present suggested model still has certain problems with algorithm stability and accuracy, though, and this need be investigated further and improved.

3.2. Optimized CFI Method. The optimization algorithm chosen in this study is based on the CFI System (CF), which enables the model to perform intelligent recommendations. The secret to this algorithm's success is its ability to compute resource and user similarities, as well as classify and limit the data to find possible user growth regions. As a result, the system can manage unstructured resource data and does away with the need for resource feature modeling. As seen in Figure 3.2, there are two types of CF algorithms: user-based and project-based.

The method will begin with the resource that the user prefers, look for items that are comparable to it, eliminate the items which have already been ensued, and then offer suggestions. Users benefit from greater freshness with the former and relative stability with the latter. Based on various practical objectives, the model should select suitable recommendation principal methods. This algorithm's benefits include the how users and feedback information interact, how easy it is to approach, and how stability improves with time. Still, this approach has a high degree of user interaction; for example, the model's calculation accuracy will drastically decrease if the user's behaviour data is poor.

This suggests that there are three main processes that make up the system's functioning: First, features are extracted and categorized using both structured and unstructured data. Formula (3.1) indicates that structural

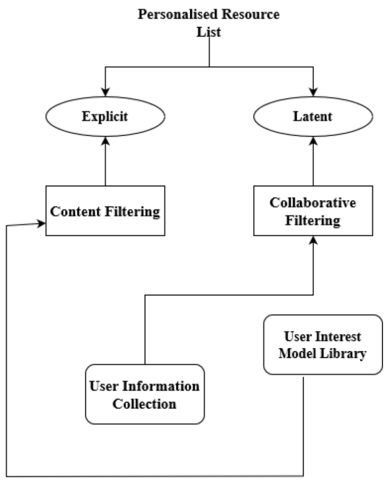

Fig. 3.2: Structure of CFI

transformation is necessary for unstructured data.

$$\begin{cases} D = \{d_1, d_2, \ldots, d_N\} \\ T = \{t_1, t_2, \ldots, t_n\} \\ d_j = \{w_{1j}, w_{2j}, \ldots, w_{nj}\} \end{cases} \tag{3.1}$$

Using the items selected as a model, the collection of articles is represented by D in equation (3.1) above. T stands for a set of items that include certain keywords. d$_j$ is the set of vectors that make up text. The total amount of items and words are denoted by N and n, accordingly. W$_{nj}$ is a representation of each keyword's value. The weight calculation method chosen by the research is the phrase recurrence inverse document frequency technique, as indicated by formula (3.2).

$$TF - IDF\left(t_k, d_j\right) = TF\left(t_k, d_j\right).log\frac{N}{n_k} \tag{3.2}$$

The average number of recurrence of the k-th word in article j is represented by the expression $TF(t_k, d_j)$ in equation (3.2) above. The total amount of items in the set with k words is denoted by n_k. Formula (3.3) thus displays the relative importance of the term in item j.

$$w_{kj} = \frac{TF - IDF\left(t_k, d_j\right)}{\sqrt{\sum_{s=1}^{T} TF - IDF(t_s, d_j)^2}} \tag{3.3}$$

CFI methods are used in this study to investigate consumers' possible interests. It is difficult to identify users having comparable preferences because multiple descriptions and other details regarding the same resources may exist in the framework. Based on this rationale, this study presents a method for calculating similarities that combines behavior and content. It is represented as a rating of similarity $sim_{grade}(u, v)$ and content similarity, respectively. Formula displays the result of the former computation.

$$sim_{grade}\left(u, v\right) = \frac{\sum i \in D_u \cap D_v \frac{1}{\log(1+|U(i)|)}}{\sqrt{|D_u|\,|D_v|}} \tag{3.4}$$

The resource's assessment variety of users u and v is denoted by D_u and D_v in equation (3.4) above, respectively. The user group that has left comments on resource d_i is represented by U (i). Formula (3.5) displays the $sim_{content}(u, v)$ content similarity between two users.

$$sim_{content}\left(u, v\right) = \frac{EM_u.EM_v}{\left|EM_u\right|.\left|EM_v\right|} \tag{3.5}$$

The data sets of two users' initial interest are represented by EM_u and EM_v, accordingly, in equation (3.5) previously. In conclusion, formula (3.6) displays the results of the mixed similarity calculation.

$$sim\left(u, v\right) = \beta sim_{grade}\left(u, v\right) + (1 - \beta)sim_{content}(u, v) \tag{3.6}$$

The weighting factor, denoted by β in equation (3.6) above, is a similar ratios variable that must be empirically determined within the interval [0, 1]. When the amount of weighting is zero, the model is sufficient to take similarities in content into account. On the other hand, the model simply must take score similarity into account if the factor to be weighted is 1. To determine the ultimate user's mixed similarity, the algorithm must first compute the score similarity and content similarity among users independently. The similarity values are then fused based on the weighting factor values.

A person who most closely resembles the user who is being targeted will be added to the neighbouring user collection, and CFI concepts will then be applied to suggest potentially interesting resources. Formulas illustrate that a feature word f_i's weight is determined in the latent preferences model.

$$w2_{uj} = \sum v_i \in U_M \frac{sim\left(u, v_i\right)}{\sum v_i \in U_u sim\left(u, v_i\right)}.w1v_{ij} \tag{3.7}$$

An efficacy test using a model simulation was carried out prior to as well as following optimization to confirm the efficacy of the optimized CFI recommendation model. Additionally, the suggested model was used on the real system for visual evaluation, revealing how many clicks and successful suggestions the model received in each week. In the meantime, the efficacy of the optimized customized recommendations model was contrasted with that of other recommendation models.

The model described in this study has a technological edge since it makes sophisticated use of the Optimized Collaborative Filtering Algorithm (CFI), which improves the model's capacity to provide individualized learning experiences. In dynamic situations such as e-commerce, traditional collaborative filtering systems frequently suffer from sparse data and scalability issues. The model used in this study, however, solves these difficulties with the help of clever recommendation algorithms that, in addition to calculating similarities between users and resources based on their interactions, also efficiently classify and filter the data to identify possible growth areas for user interest.

Through the integration of user- and project-based collaborative filtering techniques, the model is able to provide suggestions that strike a compromise between stability and freshness, accommodating user preferences while upholding the integrity of the recommendation framework. The model's input is further refined by using sophisticated data preprocessing techniques, such as TF-IDF for feature extraction from unstructured data, which makes recommendations that are more pertinent and accurate. The model is able to fine-tune its predictions through the final mixed similarity calculation, which combines behavioral and content similarities with empirically established weights. This provides a reliable solution that can be customized to unique user needs and behaviors.

Essentially, the technical complexity of the model not only overcomes the shortcomings of conventional collaborative filtering when handling sparse and complex data, but it also improves the capacity to provide customized recommendations in an educational setting, which could revolutionize the way that personalized education is approached in digital platforms.

4. Result Analysis. To address the overfitting issue, some neurons must be randomly removed. According to a review of the literature, the test and training loss curves level out, and the amount of loss drops below 0.06, indicating that the model has converged, when the number of iterations approaches 40. Accuracy can be significantly improved when compared to the standard recommendation's models CNN, FCNN-CF, and Gram-CF.

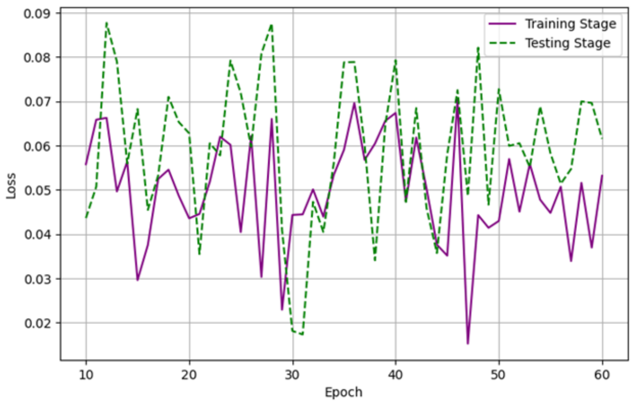

Fig. 4.1: Training and Testing Loss

To validate the model, same ecological and assessment criteria are employed. The standard method CNN bases itself on users' run information, the algorithm FCNN-CF depends on user conduct statistics, and the Gram-based revised recommendations engine Gram-CF are selected as reference model.

The F1 value, precision, accuracy, and recall rate are the evaluation metrics that are employed. Nonetheless, when contrasted with the original models, the suggested model exhibits improvements in both recall and precision. In the meantime, F1 has significantly improved. As a result, these findings demonstrate that the suggested model outperforms the CNN, FCNN-CF, and Gram-CF comparison approaches in every way. This enhancement is the result of two-dimensional feature extraction, which combines temporal and spatial information to strengthen the expressive of the features. This eliminates anomalous data and enhances the model's capacity for learning.

The first few epochs see a sharp decline in training and testing losses, indicating that the model is picking up patterns from the data quickly. Both lines exhibit some convergence following the first decline, suggesting that the pace of learning has leveled off. This is a typical stage where the model keeps becoming better. The model may not be substantially overfitting to the training data based on the reasonably close distance between the training and testing lines. Overfitting would be indicated if the training loss was significantly less than the testing loss. The variations may suggest that the model's learning is not totally stable, particularly in the testing line. In figure 4.1 shows the training and testing loss.

With each epoch, the model is learning substantially from the data, as evidenced by the high growth in both lines at the beginning. when the epochs increase, both accuracies level out, which is typical when the model gets closer to its maximum ability to learn from the available data. Usually, when both lines converge and the testing accuracy closely tracks the training accuracy, the model is not overfitting. A high training accuracy but a significantly lower testing accuracy would be indicative of overfitting. A peak in testing accuracy appears to be reached below 1.00, which may indicate that the model has performed as well as it can in terms of generalization given the present design and data. In figure 4.2 shows the training and testing accuracy.

A recommendation system based on fully convolutional neural networks with collaborative filtering (CF) is represented by this line. Recall declines as the quantity of items rises, according to the pattern. This is an example of a convolutional neural network-based recommendation algorithm. As more things are taken into consideration, the recall drops, much like the FCNN-CF. This probably refers to an approach that combines collaborative filtering with a gram matrix or feature representation. This is the suggested algorithm from the study's author(s), which is where this chart came from. It displays the recall percentage for their method, which likewise decreases with an increase in the number of objects. As there are more goods, the recall gets worse. In figure 4.3 shows the result of Recall.

This illustrates the accuracy of a collaborative filtering system with a fully convolutional neural network for varying item counts. It appears to function steadily across the range. indicative of the precision performance

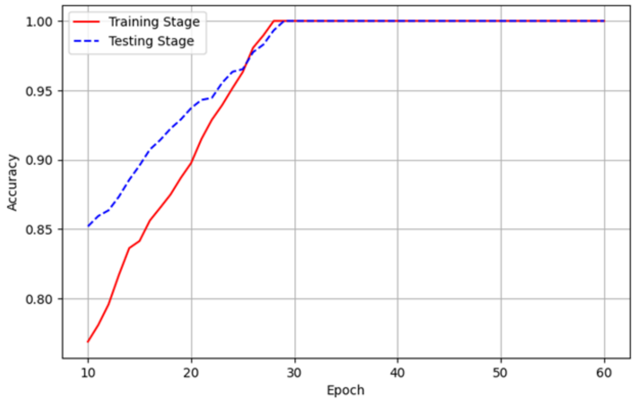

Fig. 4.2: Training and Testing Accuracy

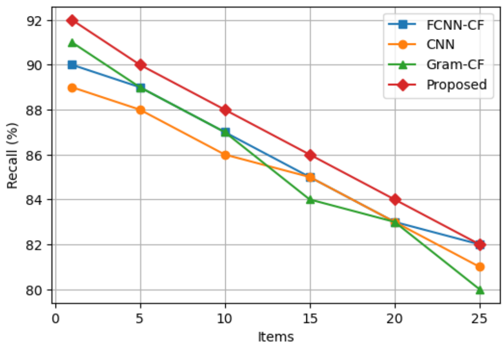

Fig. 4.3: Recall

of a conventional convolutional neural network. It exhibits a decrease as the number of items rises, much like the others. This is probably an approach that combines Collaborative Filtering with a gram matrix or some other equivalent feature representation. As additional items are added, its precision declines, which is a typical pattern in recommendation systems. This line corresponds to the accuracy of the algorithm that the graph's designers have suggested. It displays a performance comparison with the other algorithms. In figure 4.4 shows the result of Precision.

5. Conclusion. The continuous progress in the fields of science and technology, especially the development of artificial intelligence, machine learning, and other methods, has led educational institutions to begin implementing more customized content from conventional uses in the past few years. Traditional colleges and universities usually disregard each student's unique needs and educational preferences in Favor of a standardized teaching style. A personalized learning system powered by machine learning algorithms can provide tailored learning materials and recommendations based on each student's educational history, interests, and abilities, thereby improving learning outcomes. Furthermore, machine learning techniques have the potential to provide instantaneous feedback on student accomplishment and adjust educational strategies accordingly. Another challenge is ensuring that AI is used to support the broad goals of higher education, such as fostering creativity and critical thinking, rather than just removing tasks and increasing efficiency. This study looks at the various applications of the Optimized Collaborative Filtering Algorithm and artificial intelligence (AI) in higher education. Additionally, it suggests for enhancing pupils' cognitive capacities and contrasts it with various approaches that are now in use. It is shown that the proposed model performs better than the other models.

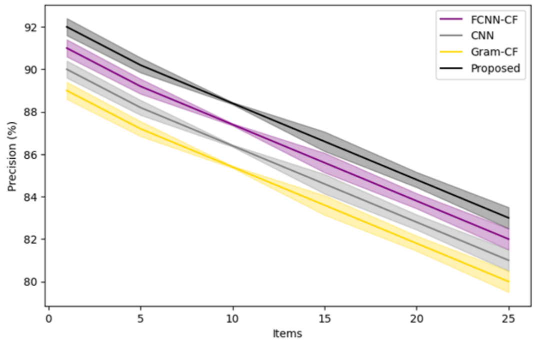

Fig. 4.4: Precision

In order to develop immersive learning environments, future research could investigate how to integrate the personalized recommendation system with AR and VR technology. This could potentially increase engagement and retention rates by enabling learners to interact more interactively with the content.

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